# Title: Leveraging data science and machine learning for urban climate adaptation in Africa: a HE2AT CENTER STUDY protocol

Authors: Christopher Jack1\*, Craig Parker2\*, Yao Etienne Kouakou3,4, Bonnie R. Joubert5, Kimberly A. McAllister5, Maliha Ilias6, Gloria Maimela2, Matthew Francis Chersich2, Sibusisiwe Makhanya7, Stanley Luchters8,10, Prestige Tatenda Makanga8,11, Etienne Vos7 Kristie Ebi9, Brama Kone3, Akbar Waljee12, Gueladio Cisse3 on behalf of the HE2AT Center  
\*Equal first authors

HE2AT Center Group (alphabetical): Abdoulaye Tall, Adja Ferdinand Vanga, Christopher Jack, Craig Mahlasi, Iba Dieudonné Dely, James Mashiyane, Lisa van Aardenne, Madina Doumbia, Nicholas Brink, Pierre Kloppers, Piotr Wolski, Sibusisiwe Makhanya, Tamara Govindasamy, Toby Kurien

Author Affiliations:

1. Climate System Analysis Group, University of Cape Town
2. Wits RHI, University of the Witwatersrand, Johannesburg, South Africa
3. University Peleforo Gon Coulibaly, Korhogo, Côte d’Ivoire
4. Centre Suisse de Recherches Scientifique, Côte d’Ivoire
5. National Institute of Environmental Health Sciences, National Institutes of Health, Department of Health and Human Services, Durham, North Carolina, United States of America
6. National Heart Lung and Blood Institute, National Institutes of Health, Department of Health and Human Services, Bethesda, Maryland, United States of America
7. IBM Research Africa, Johannesburg
8. Centre for Sexual Health and HIV & AIDS Research (CeSHHAR), Zimbabwe
9. The University of Washington, Seattle, United States of America
10. Liverpool School of Tropical Medicine, Liverpool, UK; Department of Public Health and Primary Care, Ghent University, Belgium
11. Surveying and Geomatics Department, Midlands State University, Gweru, Zimbabwe
12. Department of Internal Medicine, Gastroenterology & Hepatology, University of Michigan Medical School, Ann Arbor, Michigan, United States of America

Correspondence to Dr Christopher Jack, [cjack@csag.uct.ac.za](mailto:cjack@csag.uct.ac.za)

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ABSTRACT

**Introduction:** African cities, particularly Abidjan and Johannesburg, face challenges of rapid urban growth, informality, and strained health services, compounded by increasing temperatures due to climate change. This study aims to understand the complexities of heat-related health impacts in these cities. The objectives are: 1) mapping intra-urban heat risk and exposure using health, socio-economic, geospatial climate, and satellite imagery data; 2) creating a stratified heat-health outcome forecast model to predict adverse health outcomes; and 3) establishing an Early Warning System for timely heatwave alerts. The ultimate goal is to foster climate-resilient African cities, protecting disproportionately affected populations from heat hazards.

**Methods and Analysis:** The research will acquire health-related datasets from eligible adult clinical trials or cohort studies conducted in Johannesburg and Abidjan between 2000 and 2022. Additional data will be collected, including socio-economic, geospatial climate datasets and satellite imagery. These resources will aid in mapping heat hazards and quantifying heat-health exposure, the extent of elevated risk, and morbidity. Outcomes will be determined using advanced data analysis methods, including statistical evaluation, machine learning, and deep-learning techniques.

**Ethics and Dissemination:** The study, has been approved by the Wits Human Research Ethics Committee (reference no: 220606). Data management will follow approved procedures. Results will be disseminated through workshops, community forums, conferences, and publications. Data deposition and curation plans will be established in line with ethical and safety considerations.

(Word count: 228 )

**Keywords:** urban, heat, heatwaves, health, Early Warning Systems, intra-urban, socio-economics and environment, exposure mapping, hazard mapping, heat-related health impacts, African cities, data science and machine learning, temperature

Article Summary

Study strengths and limitations

1. Employs comprehensive data collection from clinical, socio-economic, and remote sensing sources, ensuring a multidimensional analysis of urban heat exposure.
2. Leverages state-of-the-art machine learning techniques for predictive modelling of heat-health outcomes, advancing the field of environmental health research.
3. A cross-disciplinary approach enriches the interpretation of data, linking climate science with public health implications.
4. Risk of sampling bias due to secondary data utilisation, which may influence the representativeness of findings.
5. The spatial resolution of datasets, particularly those capturing microclimatic urban variations, may limit the granularity of exposure assessments, affecting the precision in capturing heat stress metrics.

# Introduction

The HE2AT Center (HEat and HEalth African Transdisciplinary Center), a consortium spanning South Africa, Côte d'Ivoire, Zimbabwe, and the United States, embodies global collaboration. Funded through the United States NIH "Harnessing Data Science for Health Discovery and Innovation in Africa" (DS-I Africa) program, the Center amalgamates diverse expertise in pursuit of comprehensive urban climate resilience strategies[1].

This study emerges from the HE²AT Center, as a Research Project (RP) aiming to interrogate the intricate relationships of urban spaces to heat-health impacts, emphasising the need for nuanced responses. It highlights the disproportionate risks borne by residents of impoverished areas, the elderly, those with pre-existing health conditions, children, outdoor workers, and inhabitants of densely populated or informal settlements—groups for whom the urban heat island effect is a daily lived reality[2-4].

Research on heat-related health risks in Africa, including seminal works in Abidjan and Johannesburg, reveals a critical need for localised interventions. Ncongwane et al. (2021), Pasquini et al. (2020), and Wright et al. (2019) lay the groundwork, explaining the socio-economic and infrastructural factors that exacerbate heat-health vulnerabilities[5-7].

Enhanced nighttime heatwaves over African urban clusters, as investigated by Eghosa Igun et al. (2022), underline the growing threat of heatwaves exacerbated by urban heat island effects [8]. Furthermore, an assessment of the health-related impacts of urban heat Islands (UHI) in Douala Metropolis, Cameroon by Enete et al. (2017), provides insight into the localised health burdens of urban heat [9].

Building on this foundation, our study seeks to contribute to this burgeoning field by creating an effective, data-driven Urban Heat Health Early Warning System (EWS), tailored to the unique socio-demographic make-up of African metropolises. Integrating insights from recent studies, including "Human Exposure to Dangerous Heat in African Cities" by Guillaume Thibaut Rohat et al. (2019), which assesses human exposure to extreme heat conditions [10], our research aims to offer a holistic understanding and innovative solutions to mitigate these escalating health risks.

The study is structured around three primary objectives: (1) mapping intra-urban heat risks, (2) developing a heat-health outcome forecast model, and (3) establishing an EWS that empowers both policymakers and the public with actionable insights for preemptive action. These are inspired from the robust frameworks and pioneering methods established by Thiaw et al. (2022) and Chapman et al. (2022), who have significantly advanced the field of heat-health early warning systems[11, 12].

Our approach is grounded in the IPCC's hazard-vulnerability-exposure paradigm, as evidenced by the Key Concepts and Definitions in Heat Exposure Studies (Table 1). This alignment ensures consistency with the globally recognised framework and reinforces our research's applicability to the broader discourse on climate change and public health. The terms "exposure," "vulnerability," "hazard," and "adaptive capacity" are defined in Table 1, providing a clear conceptual framework for our study.

By integrating state-of-the-art machine learning techniques with comprehensive socio-economic and geospatial data as well as clinical trial/cohort health datasets, this study endeavours to provide stakeholders with a granular understanding of heat-health dynamics, ultimately aiding in the formulation of targeted interventions that can bolster the resilience of urban populations amidst the escalating challenges posed by global warming.

Table 1: Key Concepts and Definitions in Heat Exposure Studies (Aligned with IPCC Framework)

|  |  |
| --- | --- |
| **Concept** | **Description** |
| Exposure | The presence of people, livelihoods, species or ecosystems, environmental functions, services, and resources, infrastructure, or economic, social, or cultural assets in places that could be adversely affected by heat. |
| Vulnerability | The propensity or predisposition to be adversely affected encompasses various concepts and elements, including sensitivity or susceptibility to harm and lack of capacity to cope and adapt to heat. |
| Hazard | The potential occurrence of a natural or human-induced physical event or trend that may cause loss of life, injury, or other health impacts, as well as damage and loss to property, infrastructure, livelihoods, service provision, ecosystems, and environmental resources. |
| Adaptive Capacity | Population's ability to adjust to heat linked with socio-economic factors, resource access, institutional support, and social determinants of health (SDOH). Often diminished in urban poor due to limited access to cooling resources and health services. |
| Risk | The potential for adverse consequences when hazards interact with vulnerable and exposed elements. It is often represented as the probability of occurrence of hazardous events or trends multiplied by the impacts if these events or trends occur. Risk results from the interaction of vulnerability, exposure, and hazard. In the context of heat, it refers to the likelihood and severity of negative outcomes due to heat exposure, considering the vulnerability and adaptive capacity of the affected population or system. |

Figure 1: Schematic of the Early Warning System Development. This figure outlines a four-step approach to create an Early Warning System (EWS) for heat-related health risks, integrating data analysis, stakeholder engagement, and application design

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# Study setting

Abidjan, located in Côte d'Ivoire, and Johannesburg, in South Africa, are cities experiencing rapid urbanisation—defined as the population shift from rural to urban areas along with the corresponding change in land use—compounded with stress on health services and increasing temperatures owing to climate change [13-15]. In Johannesburg, a diverse metropolis of 6.1 million people, HIV/AIDS, tuberculosis, and non-communicable diseases pose significant challenges. These are intensified by urbanisation, socio-economic disparities, and broader social determinants of health (SDOH) like education and employment [15-17]. Areas with less vegetation and higher levels of poverty face greater heat impacts, a reflection of the 'Green Apartheid' that characterises the city's urban forest and its accessibility. [18]​​. Similarly, in Abidjan, an economic centre with a population of 6.3 million, diseases such as malaria and non-communicable diseases are driven by urbanisation and wider SDOH [19-21].

Both cities represent Urban Heat Islands (UHI), a phenomenon where urban areas exhibit higher temperatures than their rural surroundings due to human activities[22] [23]. While Johannesburg's extensive urban forest offers some respite, Abidjan's Cocody district is increasingly experiencing the UHI effect due to accelerated urbanisation and land use modifications. These evolving urban landscapes underscore the requirement for holistic health strategies in both cities[24].

Abidjan and Johannesburg were selected for this study due to their unique characteristics and data availability. As cities with high population density and experience rapid urbanisation, Abidjan and Johannesburg representat the challenges facing many African cities in the context of climate change and heat-related health impacts. Additionally, these cities have access to critical detailed health data from clinical trials and cohort studies. Both cities therefore enable a focused examination of heat-related health risks in urban African settings, potentially informing broader regional strategies for climate adaptation and public health.

# Methods

The study plans to combine datasets from many sources encompassing various fields—health, climate, environment, and SDOH. This multi-faceted approach will aid in building more thorough and locally pertinent models of heat-related health outcomes. These models will consider the diverse range of day-to-day realities and experiences encountered by inhabitants within each city, capturing how they impact their health in the context of heat [25]. In this study, 'lived experiences' refers to individuals' unique daily conditions, challenges, and opportunities, shaped by their specific SDOH and environmental circumstances. Additionally, multiple datasets within a particular domain (e.g., multiple health trial datasets) both increase the statistical sample sizes for more robust modelling as well as enable a rigorous quantification of key uncertainties (e.g., multiple climate datasets) [26, 27].

* 1. Socio-economic and environmental data

This research will collect socio-economic geospatial data, which includes information on household economic conditions, service availability, and residential characteristics—referring to factors like housing type, construction materials used, and the quality and condition of living spaces [28]. The data will include national census records, specialised household, and demographic surveys and encompass details about individual and household income, education, occupation, living circumstances, and accessibility to healthcare, education, and transportation services. [29] For Johannesburg, key variables for the study will be provided by the Gauteng City-Region Observatory (GCRO) datasets. In the case of Abidjan, equivalent data will be sourced from the National Institute of Statistics (INS) of Côte d'Ivoire, which provides comprehensive socio-economic and demographic data [29, 30].

Remote sensing data will be retrieved from satellite sensors, including optical images and indicators of physical aspects such as land surface temperature, soil moisture, vegetation condition, and land use and coverage [31]. Where available, researchers will amalgamate data from current sensor networks with urban land use and building density details to create a model of urban land use heat [28, 29]. Although Landsat and MODIS data primarily measure land surface temperature (LST), statistical models can estimate air temperature from remotely sensed LST. However, it should be noted that LST may not fully capture heat stress experienced in urban areas. In this study, appropriate statistical models will be used to indirectly retrieve air temperature from the LST data provided by Landsat and MODIS, and where possible, we will incorporate humidity data to provide a more comprehensive assessment of heat stress [32].

Climate-associated data will be sourced from open data repositories, such as the Copernicus Climate Data Store (CDS) and Earth System Grid Federation (ESGF), offering observational-based datasets, historical re-analyses, and climate simulations While the Copernicus Climate Data Store (CDS) and Earth System Grid Federation (ESGF) provide valuable climate data, their spatial resolution may not be sufficient to distinguish different parts within the city[33]. To address this limitation, we will employ downscaling techniques to enhance the spatial detail of our geospatial climate data. Specifically, we will explore the use of dynamic downscaling with high-resolution climate models such as the Weather Research and Forecasting (WRF) model and the UrbClim urban climate model. These models offer detailed results on heat stress for cities, allowing for a more precise analysis of intra-urban heat variations and can improve the accuracy of our heat risk assessments for Johannesburg and Abidjan [34, 35].

Additionally, the IBM-PAIRS platform will be employed as a source of climate data, including data from climate models, weather stations, and satellite observations[36]. To further enhance our analysis, we will integrate datasets from the European Space Agency's WorldCover portal and the Global Human Settlement Layer (GHSL), which provide detailed land cover and human settlement data, respectively[37, 38]. This will provide a comprehensive snapshot of Africa's past and future climate conditions, including heat waves' frequency, duration, and intensity.

* 1. Health trials and cohort data

The health data for this study will be collected from clinical trials and cohort studies, such as HIV drug trials and COVID-19 vaccine trials. These studies typically involve many participants (hundreds to thousands), are conducted over an extended period (multiple years) within a specific geographical area. They provide detailed longitudinal individual health data for building statistical models relating time-varying predictors to health outcomes. Potential outcomes of interest include cardiovascular events, respiratory issues, kidney conditions, and mental health impacts, which may be exacerbated by heat exposure in urban environments[39].

More specifically, the health cohort data integrated into the study will be identified based on the availability of three classes of variables within each study:

* Clinical variables: including vital signs (e.g., body temperature, blood pressure, and heart rate), indicators of heat-related illness (e.g., headache, dizziness, fatigue, and nausea), and details on pre-existing medical conditions (e.g., hypertension, diabetes, and cardiovascular disease) that could increase the risk of heat-related illness, and documentation of adverse events potentially related to heat exposure.
* Laboratory variables: including blood tests (e.g., electrolyte levels, liver and kidney function tests), markers of inflammation and oxidative stress, as well as HIV tests, including viral load and CD4 count, and COVID-19 test results.
* Demographic and SDOH variables: involving basic demographic information (e.g., age, sex, race, and ethnicity), socio-economic factors (e.g., education, income, and occupation), and data on housing and urban infrastructure (e.g., air conditioning availability, ventilation, and shading) that could influence heat exposure and the degree to which individuals and households are at an increased risk.

In response to the shifts in mortality and morbidity during the 2020-2022 COVID-19 pandemic, we will analyse data separately for pre-pandemic, pandemic, and post-pandemic periods. Additionally, we will include COVID-19-related variables as covariates in our models to control for the pandemic's impact on health outcomes.

Table 2: Summary of Data Sources for each Objective

|  |  |
| --- | --- |
| **Objective** | **Data Sources** |
| 1. Mapping intra-urban heat risk and exposure | - Socio-economic data (census, surveys, GCRO datasets)  - Geospatial data (land use, building density, OpenStreetMaps)  - Climate data (WRF, UrbClim models, downscaled CDS & ESGF data, IBM-PAIRS platform) |
| 2. Creating a stratified heat-health outcome forecast model | - Health data with clinical variables (e.g., vital signs, heat-related illness indicators)  - High-resolution urban temperature hazard maps (Landsat, MODIS data with statistical models for air temperature estimation)  - Remote sensing data (satellite imagery, land surface temperature, soil moisture, vegetation condition)  - Socio-economic and environmental data (household economic conditions, service availability, residential characteristics) |
| 3. Establishing an Early Warning System | - Integrated health and socio-economic data  - Geospatial heat hazard maps  - Health outcome forecast model outputs  - COVID-19 incidence and mortality rates (for pandemic period adjustment)  - Risk profile data (demographic groups, health conditions, locations, socio-economic statuses) |

* 1. Integration of datasets

Our study relies on integrating socio-economic, clinical, environmental, and geospatial data to understand heat's impact on health in African cities. We will cross-reference health trial participant geolocations with socio-economic and environmental data, applying spatial jittering to protect privacy while retaining spatial trends. Additionally, we'll incorporate remote sensing and climate data to examine how environmental changes affect health outcomes related to heat exposure.

In pursuit of our research objective to explore the correlation between heat and health within the urban environments of Johannesburg and Abidjan, we have developed a comprehensive strategy to identify relevant clinical trials and cohort studies systematically. This strategy involves searching key databases using a combination of MeSH (Medical Subject Headings) and free-text terms, including study location, diseases of interest, the number of participants, study type, collected data, and the timeframe of study conduction. Our targeted search terms are designed to retrieve studies that provide robust clinical, laboratory, and demographic data relevant to the impact of heat on health outcomes.

A two-step process of dual independent review will be employed for post identification of potentially relevant studies. Initially, studies will be screened based on their titles and abstracts. Subsequently, studies deemed potentially eligible will be procured in their full-text format for a more thorough assessment against our pre-defined selection criteria (Table 1).

The quality of the selected studies will be evaluated by health researchers through a peer-reviewed tracking tool to ensure their scientific soundness and reliability. The data will be collated, synthesised, and any discrepancies, will be addressed and resolved through consensus discussions among team members.

The following criteria outlined in Table 1 will be used to select research projects to be considered for inclusion in our study.

**Table 3: Eligibility Criteria for Research Project 2**

|  |  |
| --- | --- |
| Criteria | Description |
| Study type | Cohort or trial with at least 200 adult participants |
| Study location | Johannesburg or Abidjan, or both cities |
| Study design | Randomised or non-randomised clinical trial, or observational or interventional cohort with prospectively collected data |
| Data collected | At least two of the clinical or lab variables |
| Ethics approval | Local ethics approvals obtained |

For the success of this project, access to relevant trials and cohort data is crucial. In the event of data unavailability or sharing restrictions, we have contingency plans to ensure the project's progression. These include exploring alternative data sources such as the National Health Laboratory Service (NHLS), adjusting the study's scope, and utilising synthetic data if necessary.

* 1. Managing bias

Managing potential biases is critical to ensuring our study's integrity and robustness as outlined by the following strategy .

Primarily, our approach will involve carefully selecting health data sources, ensuring they meet established quality criteria and represent diverse demographic and geographic segments within our target cities of Johannesburg and Abidjan. This strategy will assist us in avoiding selection bias that could skew our findings [40].

We will adjust the analysis phase when potential biases are identified. Specific statistical methods like propensity score matching, inverse probability weighting, and stratification will be applied. These methods help to control for confounding variables and reduce bias in observational studies, increasing the validity of our outcomes [41].

* 1. Objective One: Assessing the degree of increased risk within cities

The primary goal of our research is to assess and illustrate the socio-economic and environmental factors that increase risk, in conjunction with exposure to heat hazards as defined in table 1 , in two African cities. We will utilise the comprehensive datasets described earlier to accomplish this.[42-44]

In our study, we have opted for Principal Component Analysis (PCA) for dimensionality reduction due to its interpretability and computational efficiency, essential for our large datasets. PCA ranks new uncorrelated components by explaining variance, aiding in identifying key factors. Although PCA's linearity may miss nonlinear patterns, and its variance-based importance assumption may not align with the context of heat-related health risks, PCA's robustness makes it suitable for initial high-dimensional data exploration..

* 1. Objective Two: Creating a geographically and demographically stratified heat-health outcome forecast model

The second objective of this study is to construct a geographically and demographically stratified heat-health outcome forecast model designed to predict adverse health outcomes at varying temperature thresholds for different populations and neighbourhoods.

This involves the creation of high-resolution urban temperature hazard maps . We will utilise remote sensing, statistical downscaling, and combined modelling to derive near-surface air temperatures from Landsat and MODIS data [45]. For instance, Gudmundsson and Seneviratne (2021) demonstrated using such models to predict air temperature from LST data. Therefore, while Landsat and MODIS data are not direct measures of air temperature, they can be indirectly used for air temperature retrieval by applying an appropriate statistical model [32].

These temperatures will then be validated using weather station records and land-use maps. The resulting heat hazard maps will serve as a critical input for the subsequent stages of our machine learning pipeline.

Once generated, the temperature hazard maps will be integrated with health datasets. This combined dataset will then undergo feature engineering. Feature engineering is a crucial step in machine learning and involves selecting and transforming relevant predictors that better represent the underlying data patterns [46]. The features will be derived from the high-resolution temperature hazard fields and spatially disaggregated variables from the health datasets.

With the features engineered, we will apply various standard machine learning models, such as decision trees, linear and quantile regression trees, support vector machines, and logistic regression [47]. These models are chosen for their proven effectiveness in capturing relationships in complex datasets.

Additionally, we will explore deep recurrent neural networks, specifically Gated Recurrent Units (GRUs) and Long Short-Term Memory (LSTM) networks, due to their ability to model temporal dependencies in time-series data, which is essential for predicting heat-related health outcomes. While these models are state-of-the-art in computer science, their application in heat-health studies is still emerging as demonstrated in a review of recent literature, including studies by Boudreault et al. (2023, 2024), Wang et al. (2023, 2021, 2020), Lee et al. (2022), and Nishimura et al. (2021) [48-54]. However, recognising that simpler statistical models may be effective, we plan build on work by Boudreault et al.(2024), to compare the performance of deep learning models with tree-based approaches and nonlinear statistical models in our analysis [50].

Throughout this process, we will assess the significance of predictors for different populations within the two cities. This will allow us to identify varying susceptibility levels to heat-induced health conditions based on demographics and risk factors. Potential health co-morbidities to be explored include cardiovascular disease, respiratory disease, renal disease, and HIV status [55].

We will use k-fold cross-validation to assess model performance and generalizability, train models on a designated set, and calibrate them with grid or random search techniques. Validation will occur on a separate set to evaluate generalisation, using metrics like accuracy, precision, recall, F1 score, MSE, and MAE. Special attention will be paid to model performance during heatwave periods to ensure effectiveness in predicting heat-related health outcomes.[56]

An iterative process of model refinement and validation will ensure the ongoing relevance of our model and enable us to continually improve the model's performance and maintain its applicability to the evolving urban heat-health landscape [57].

* 1. Sample size considerations for health datasets

To ensure our models' robustness and accuracy, a comprehensive, four-step approach will determine the required sample size for our health datasets. Based on documented best practices (see Riley et al. in BMJ (2020)), this approach will consider factors like the number of predictor parameters, event prevalence, anticipated model performance, and overfitting prevention strategies. Our methodology is adaptable to various outcome types, including continuous, binary, and time-to-event data, ensuring our predictive models are statistically robust and clinically relevant. By rigorously applying this tailored procedure to health data, we aim to build models that accurately capture the target populations' heat-health dynamics and risk profiles​.[58]

Figure 2: Methodology to create a spatially and demographically stratified heat-health outcome forecast model

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* 1. Objective Three: Develop an Early Warning System reflective of geospatial and individualised risk profiles

The third objective is to develop an Early Warning System (EWS) that integrates geospatial and individualised risk profiles of heat-related health impacts in Abidjan and Johannesburg, as depicted in Figure 2. The EWS aims to provide actionable insights to stakeholders, including community health workers, clinic managers, urban planners, and at-risk individuals. It combines high-resolution heat hazard maps and a forecast model to generate alerts for areas with predicted adverse heat-health outcomes. This involves refining the forecast model, merging it spatially with heat hazard maps, and generating timely alerts. The EWS also incorporates heat hazard predictions for proactive risk management, offering tailored guidance for at-risk individuals on hydration and activity scheduling. Inspired by the Ahmedabad Heat Action Plan, our system emphasises inter-agency coordination and community outreach for effective heat risk mitigation [59].

While our EWS aims to provide advanced warnings, we acknowledge the challenges of long-term forecasting. The accuracy of predictions depends on data reliability, model complexity, and weather variability. Continuous model refinement is essential for improving predictive capabilities.

* 1. Patient and Public Involvement Statement

Public and patients input is integral to our study, especially informing our Early Warning System design. This input guide risk mitigation strategies and the development of user-friendly, actionable digital tools.

* 1. Project timeline

The project is funded to run from 2022- 2026.

# Ethical approval and protection of human subjects

This research study received ethical approval from both the Wits Human Research Ethics Committee in Johannesburg (reference number 200606) on June 30, 2022, and the National Ethics Committee for Life and Health Sciences, Côte d'Ivoire, on November 25, 2022 (reference number 176-22/MSHPCMU/CNESVS-kp) and will follow the United States Department of Health and Human Services regulations for the protection of human subjects in research (45 CFR 46). Our research protocol has two critical ethical and legal considerations: informed consent for secondary data usage and the protection of potentially identifiable information.

Regarding informed consent for secondary data usage, we will critically examine the consent procedures intended for the original study. If a participant has previously provided "broad consent", permitting the use of their data in future research endeavours, we can share their data without additional ethical approvals. For participants who have granted "narrow consent, " which restricts data sharing beyond the original study purpose careful deliberation is required. If obtaining renewed consent is unfeasible or involves a disproportionate effort, we will seek an informed consent waiver from the appropriate ethics committee.

In order to protect potentially identifiable information and minimising privacy risks (such as indirect identifiers like geographical data in the collleacted data) we will employ several protective measures including the restriction of identifiable data and no use of real names or other identifying factors. Data will be stored in a password-protected server with limited access. Additionally, following data minimisation principles, we will retain only the data essential for achieving our study objectives. When applicable, we will anonymise data through geographical aggregation and jittering, especially when home addresses are used.

Finally, we acknowledge the specific legislative requirements for using health data in different countries, including the laws surrounding the cross-border transfer of such data. We will, therefore, require data providers to provide a contractual guarantee, as part of the data sharing agreement, that all original studies followed appropriate informed consent procedures and that the sharing of this data complies with all relevant data protection laws.

# Study oversight

Prof. Chersich, Prof. Luchters, and the Hub Administrator direct the HE2AT Center. Steering Committee members represent six South, East, and West African institutes. This study is led by Prof. Cisse of Ivory Coast's Peleforo Gon Coulibaly University and co-led by Dr Christopher Jack of the University of Cape Town.

# Dissemination

To maximise HE2AT Center's effectiveness, prompt dissemination of research findings is crucial. We devised a strategy detailing publication types, authors, and release dates. Our findings will be shared with research and relevant working partners to inform various levels of activities and update recommendations as needed. Timely dissemination is vital to HE2AT Center's success and mission.

# Study status

Ongoing.

# Author Contributions**:**

GC, MC, CJ, and SL were involved in the conception and design of the research. CP, MC and GM obtained ethics approval. CP, MC and SL prepared the figures. CP, CJ drafted the manuscript. All authors were involved in design and discussions to implement the protocol. All authors also edited and revised the manuscript. All authors approved the final version of the manuscript.

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# Competing interests

The authors declare potential competing interests: MF, GM, and CP have pension fund investments in the fossil fuel industry. The University of the Witwatersrand holds endowments and financial reserves invested in the same industry.

Data sharing statement:  In accordance with the NIH data sharing policy, data from the HEAT002 study will be made available to the scientific community. Researchers interested in accessing this data should submit a detailed request to Chris Jack at [cjack@csag.uct.ac.za](mailto:cjack@csag.uct.ac.za). The request will be reviewed and data will be shared subject to the approval of the request, ensuring the purpose aligns with ethical standards and the privacy of the participants is protected.

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